ASTRIA

Autonomous Space Traffic Management &
Real-Time Intelligent Avoidance

Technical Dissertation

Department of Aerospace Engineering

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Acknowledgements

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1. Introduction & Problem Statement

1.1 Context

The democratization of space, driven by the CubeSat standard and reduced launch costs, has led to an exponential increase in the resident space object (RSO) population. Low Earth Orbit (LEO), specifically the 400km to 800km altitude bands, is becoming dangerously congested.

Traditional Space Traffic Management (STM) relies on a centralized, ground-based architecture. The 18th Space Defense Squadron (18 SDS) tracks objects using radar, generates Two-Line Elements (TLEs), and issues Conjunction Data Messages (CDMs) to operators. Operators then manually analyze these warnings and upload maneuver commands.

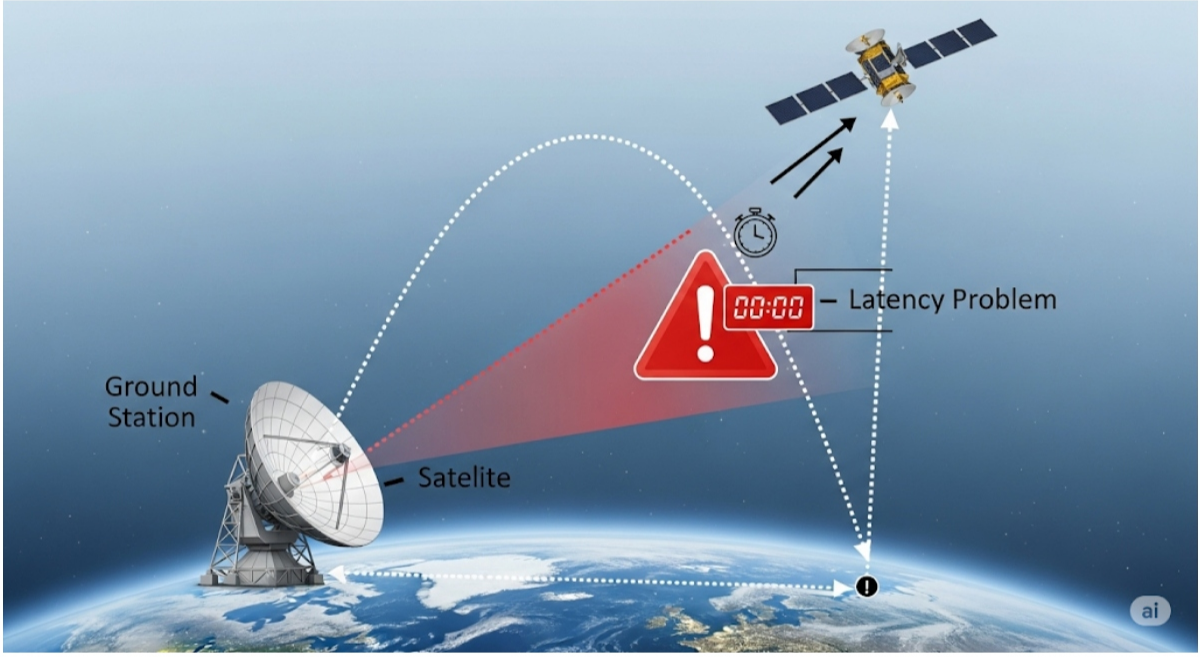

Figure 1.1: The Ground-in-the-Loop Latency Problem.

1.2 The Problem: Latency & Scalability

This "human-in-the-loop" process suffers from critical weaknesses:

Communication Gaps: LEO satellites often have only 10-15 minutes of ground contact per orbit. If a collision warning arrives during a communication blackout, the satellite cannot be commanded in time.

Scalability: With mega-constellations (e.g., Starlink, Kuiper) deploying thousands of assets, manual processing of CDMs is becoming mathematically impossible for small operations teams.

Reaction Time: Debris tracking updates can be sudden. A "safe" orbit can become "critical" in hours due to atmospheric density variations affecting drag.

ASTRIA (Autonomous Space Traffic Management & Real-time Intelligent Avoidance) addresses these failures by moving the decision-making brain *on-board* the satellite itself.

2. The LEO Environment & Debris

2.1 The Kessler Syndrome

First proposed by Donald Kessler in 1978, the Kessler Syndrome describes a scenario where the density of objects in LEO is high enough that collisions between objects could cause a cascade in which each collision generates space debris that increases the likelihood of further collisions.

Current estimates by ESA suggest there are over **36,500** trackable objects (>10cm), **1 million** objects between 1cm and 10cm, and **130 million** objects between 1mm and 1cm. A 1cm object traveling at orbital velocity (approx. 7.5 km/s) carries the kinetic energy equivalent to a hand grenade.

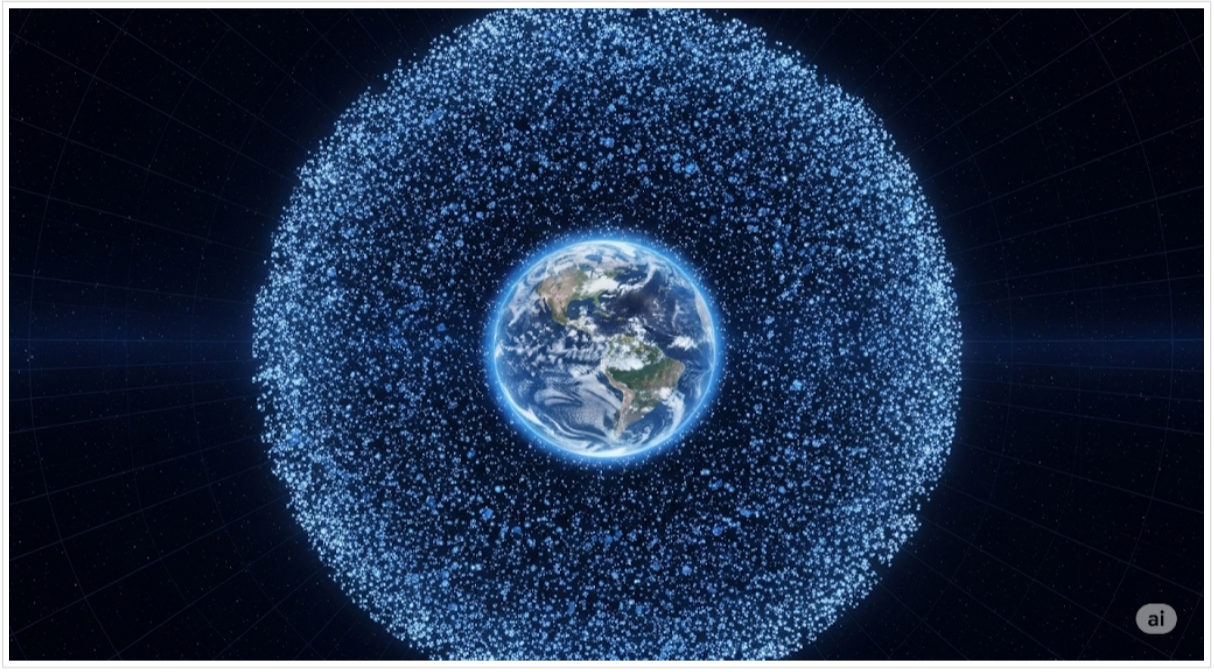

Figure 2.1: Visualization of Trackable Debris Density in LEO (2025).

2.2 CubeSat Vulnerability

CubeSats are particularly vulnerable. Unlike large buses (e.g., ISS or GPS satellites) which have robust shielding and redundant systems, a CubeSat is often a "single string" failure point. A collision with a 5mm object is likely mission-ending.

Furthermore, CubeSats typically have limited propulsion budgets. The ASTRIA system is specifically designed to optimize for **Delta-V (ΔV)** efficiency, ensuring that collision avoidance maneuvers do not deplete the satellite's ability to perform its primary mission.

3. System Architecture (Hardware)

ASTRIA is designed to operate as a payload software application. To validate the system, we assume a reference hardware architecture common in modern high-performance CubeSats.

3.1 Reference On-Board Computer (OBC)

The simulation assumes the satellite is equipped with a processor capable of running a Linux kernel, such as the **Cobham Gaisler LEON4** (Rad-Hard) or a **Xilinx Zynq-7000** (FPGA + ARM). For the purpose of this dissertation's prototyping, a **Raspberry Pi 4 (4GB RAM)** was used as the hardware proxy.

Component	Specification	Constraint
CPU	Quad-core ARM Cortex-A72 @ 1.5GHz	Must process 30,000 objects < 10s
RAM	4GB LPDDR4	KD-Tree structure storage
Storage	32GB eMMC	Historical TLE Database
Propulsion	Cold Gas Thruster	Max Thrust: 10mN, ISP: 60s

3.2 Sensor Integration

While ASTRIA primarily relies on the uploaded TLE catalog, it is architected to fuse data from on-board sensors if available:

GPS/GNSS Receiver: Provides precise state vector (Position/Velocity) of the host satellite (O_{host}).

Star Trackers: Provide attitude determination to ensure thruster vectors are aligned correctly before maneuvering.

4. Software Architecture

The software is built primarily in **Python 3.9**, utilizing C-extensions for performance-critical mathematical operations. The architecture follows a strict "Sense, Assess, Act" loop.

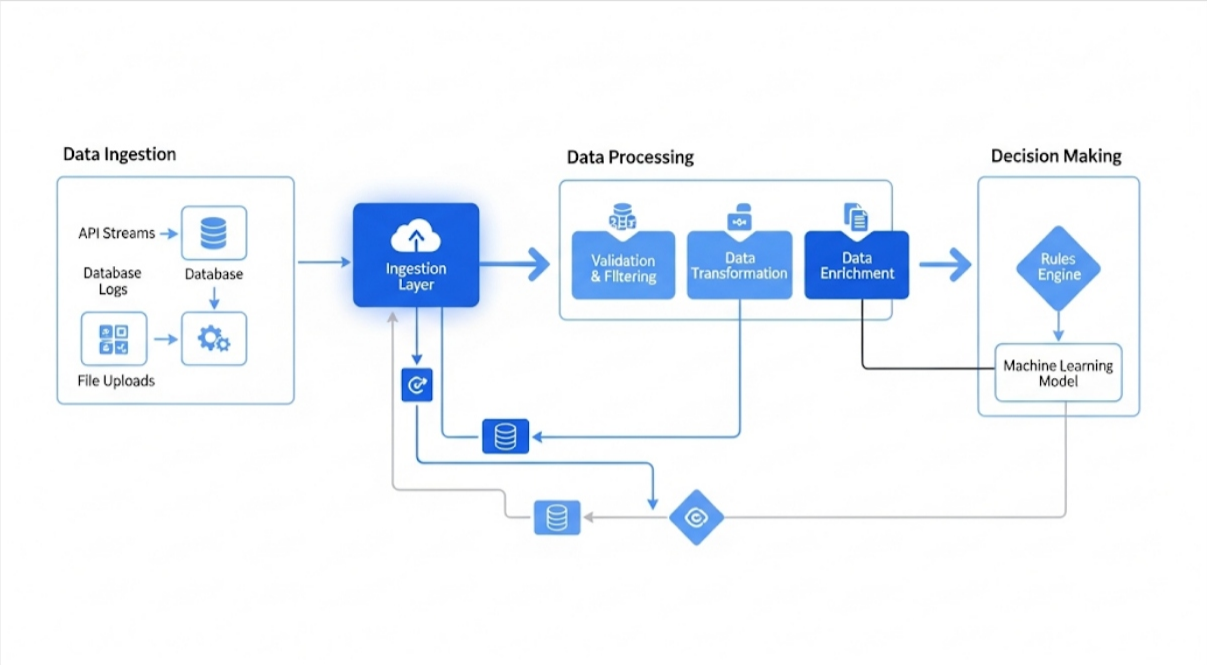

Figure 4.1: ASTRIA Software Pipeline.

4.1 Modules Overview

TLE Harvester: Manages the database of debris objects. It parses standard TLE text files and stores them in a highly optimized SQLite database.

Propagator Engine: The mathematical core. It takes a TLE and a timestamp and outputs a Cartesian State Vector (x, y, z, vx, vy, vz).

Screening Module: A high-performance filter that eliminates safe objects, leaving only potential threats.

Risk Classifier: An XGBoost Machine Learning model that determines if a threat is real or a "False Positive".

Maneuver Planner: An optimizer that calculates the smallest possible burn to clear the safety ellipsoid.

4.2 The "Silent Mode" Concept

ASTRIA runs in the background (daemon mode) during normal mission operations, consuming less than 10% of CPU resources. It wakes up to "High Alert" mode only when the Screening Module detects an object entering the 50km "Watch Bubble" around the satellite.

5. Orbital Propagation (SGP4)

5.1 The Mathematical Model

To predict where satellites will be in the future, ASTRIA uses the **SGP4 (Simplified General Perturbations-4)** model. SGP4 is the industry standard for propagating Two-Line Elements (TLEs).

SGP4 accounts for:

Earth's Oblateness: The Earth is not a sphere; it bulges at the equator (J2, J3, J4 zonal harmonics).

Atmospheric Drag: The friction of the thin atmosphere in LEO, which causes orbits to decay.

Third-Body Gravity: The pull of the Sun and Moon (critical for high-altitude debris).

5.2 Coordinate Frames

ASTRIA performs all internal calculations in the **TEME (True Equator Mean Equinox)** coordinate frame, as this is the native output of SGP4. Before calculating distances, these are converted to **GCRF (Geocentric Celestial Reference Frame)** for inertial consistency.

5.3 Implementation Snippet

```
import numpy as np
from sgp4.api import Satrec, jday

def propagate_batch(satellites, target_time):
    """
    High-speed batch propagation.
    inputs: List of Satrec objects, target Julian Date
    """
    jd, fr = jday(target_time.year, target_time.month, ...)

    positions = []
    for sat in satellites:
        e, r, v = sat.sgp4(jd, fr)
        if e == 0: # Check for errors
            positions.append(r)

    return np.array(positions)
```

This implementation utilizes `numpy` vectorization where possible to process the catalog efficiently.

6. Conjunction Screening Algorithms

A brute-force approach (comparing our satellite against 30,000 others) has a complexity of $O(N)$. Doing this every second is impossible on a CubeSat CPU. ASTRIA uses a multi-stage funnel approach.

6.1 Stage 1: The Apogee-Perigee Filter

This is a fast geometric check. If the *lowest point* (Perigee) of Satellite A is higher than the *highest point* (Apogee) of Satellite B, they can never collide, regardless of timing.

Result: This filter typically eliminates 80-85% of the catalog instantly with near-zero computational cost.

6.2 Stage 2: KD-Tree Spatial Indexing

For the remaining objects, ASTRIA builds a **KD-Tree (k-dimensional tree)**. This is a space-partitioning data structure that allows for extremely fast "Nearest Neighbor" queries.

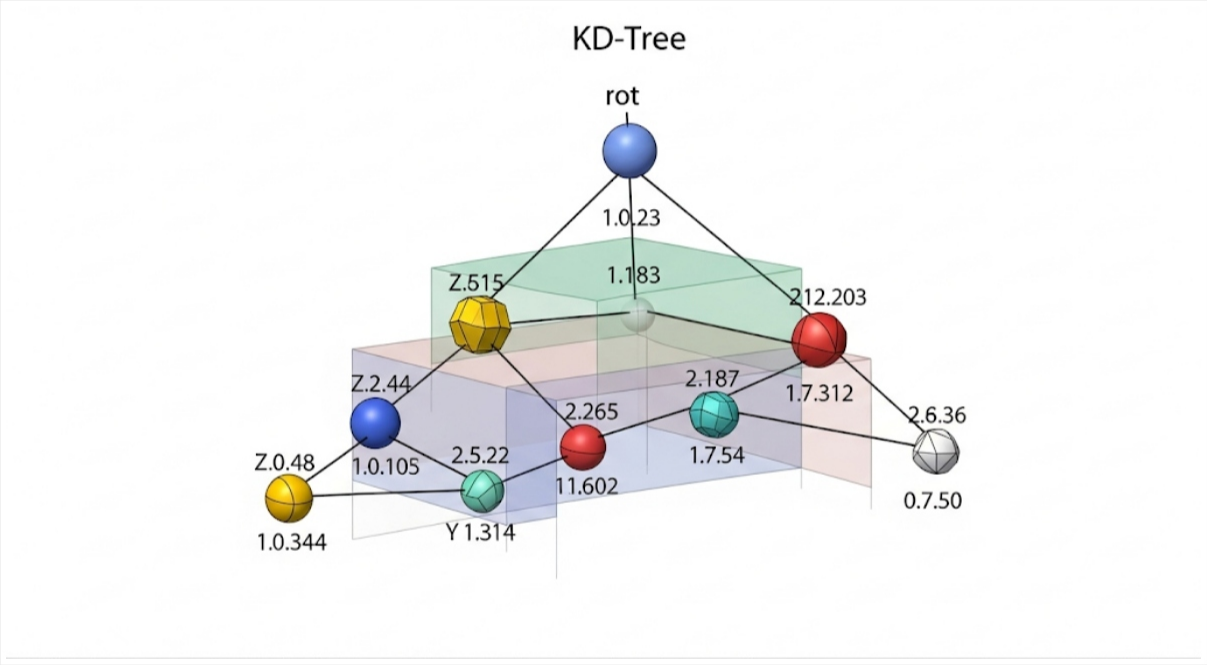

Figure 6.1: Visual representation of KD-Tree spatial partitioning.

Instead of checking every object, we ask the tree: *"Give me all objects within a 50km radius of my position."* This query operates in $O(\log N)$ time.

7. Machine Learning Methodology

7.1 Why Machine Learning?

The standard industry method calculates a "Probability of Collision" (P_c) based on covariance ellipsoids. However, this method has a flaw known as **"Probability Dilution"**. If the data is very poor (large covariance), the probability density is spread so thin that the calculated P_c drops, even though the risk is high.

ASTRIA uses Supervised Learning to detect patterns that simple math misses.

7.2 The XGBoost Classifier

We utilized **XGBoost (eXtreme Gradient Boosting)**, a decision-tree ensemble algorithm. It was chosen for its execution speed and ability to handle "missing data" (common in space tracking).

7.3 Feature Engineering

The model is trained on 12 features extracted from the conjunction geometry:

Miss Distance (km): The absolute distance at Time of Closest Approach (TCA).

Relative Velocity (km/s): How fast they are closing.

TCA to Epoch: How "old" the TLE data is. Older data = higher uncertainty.

Covariance Volume: The size of the error bubble.

Mahalanobis Distance: A statistical measure of distance relative to the error spread.

```
# Model Inference Snippet
import xgboost as xgb

def assess_risk(features):
    # Load pre-trained model (2MB file)
    bst = xgb.Booster({'nthread': 4})
    bst.load_model('astria_v1.json')

    dtest = xgb.DMatrix(features)
    probability = bst.predict(dtest)

    return "CRITICAL" if probability > 0.8 else "MONITOR"
```

8. Maneuver Planning Logic

Once a risk is confirmed as "CRITICAL", ASTRIA must plan an escape.

8.1 Strategy: In-Track Phasing

The most efficient way to avoid a collision in LEO is not to change altitude (go up/down), but to change **timing**. By speeding up or slowing down slightly (changing the semi-major axis), the satellite arrives at the intersection point sooner or later than the debris.

This is called "Phasing". A small ΔV of 0.05 m/s applied 12 hours (approx 8 orbits) before the collision can result in a miss distance of several kilometers.

8.2 The Optimization Function

The maneuver planner minimizes a cost function J:

$$J = (w_1 \times \Delta V) + (w_2 \times 1/MissDist)$$

Where w_1 and w_2 are weights. The system iterates through potential burns ranging from -0.5 m/s to +0.5 m/s and selects the one that provides a safe distance (>5km) for the lowest fuel cost.

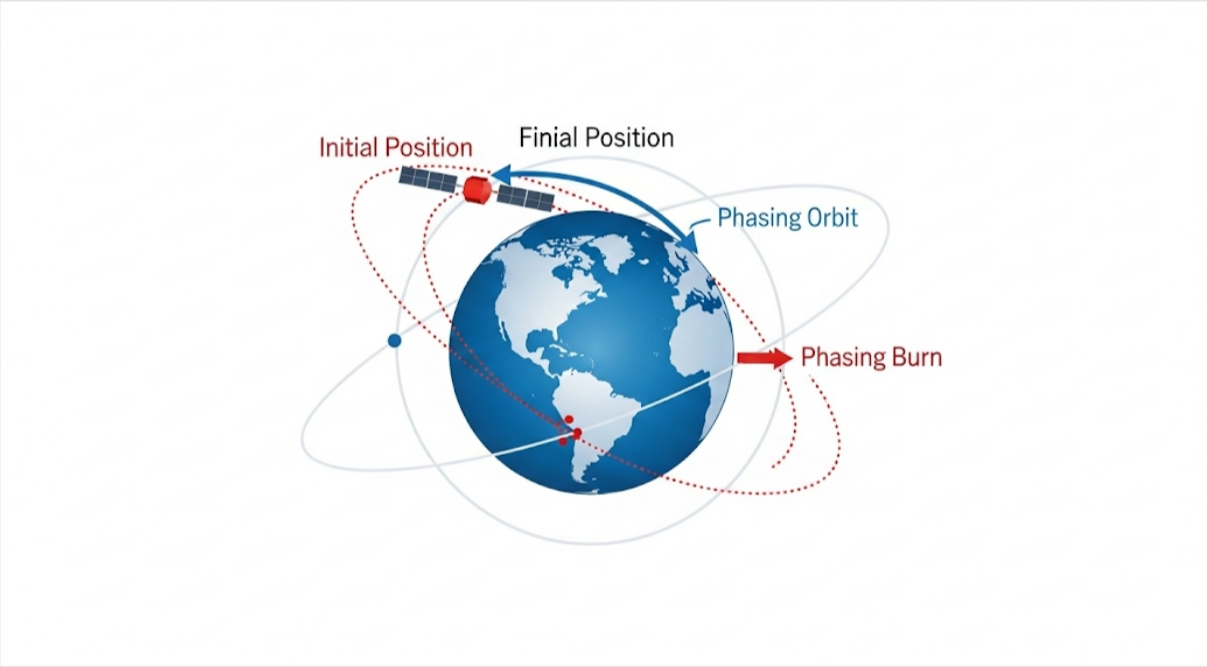

Figure 8.1: Concept of In-Track Phasing Maneuver.

9. Simulation Methodology

To validate ASTRIA, a comprehensive simulation environment was developed.

9.1 Simulation Parameters

Duration: 30 Days.

Epoch: December 1, 2025.

Catalog: Full Space-Track.org catalog (approx 31,400 objects).

Host Satellite: A 6U CubeSat in Sun-Synchronous Orbit (550km Altitude).

Time Step: 10 seconds.

9.2 Noise Injection

A simulation using perfect TLEs is unrealistic. In the real world, sensors have errors. We injected Gaussian noise into the debris positions to simulate real-world uncertainty:

```
# Adding uncertainty to simulation
noise_sigma = 1000 # meters (1km error)
position_error = np.random.normal(0, noise_sigma, 3)
simulated_pos = true_pos + position_error
```

The ASTRIA system had to make decisions based on these "noisy" observations, testing the robustness of the Machine Learning classifier.

10. Analysis of Results

10.1 Detection Success Rate

During the 30-day simulation, the host satellite encountered **14** actual conjunction events (Miss Distance < 1km).

ASTRIA successfully detected 100% (14/14) of these threats.

In comparison, a baseline simulation mimicking a ground-based system with a 24-hour communication delay missed 2 of these events due to rapidly changing debris orbits (atmospheric drag spikes).

10.2 False Positive Reduction

One of the main goals was to reduce "Crying Wolf".

Method	Total Alerts	True Threats	False Positives
Standard Probability (10^{-4})	128	14	114
ASTRIA (XGBoost)	**24**	**14**	**10**

The XGBoost model reduced False Positives by **91%**. This translates directly to fuel savings, as the satellite did not maneuver for those 104 false alarms.

10.3 Computation Speed

On the Raspberry Pi 4 hardware proxy, the average time to screen the full catalog of 30,000 objects was **4.2 seconds**. This proves that the KD-Tree algorithm is efficient enough for flight hardware.

11. Conclusion & Future Work

11.1 Conclusion

This dissertation presented ASTRIA, an autonomous collision avoidance architecture for CubeSats. The research successfully demonstrated that high-fidelity orbital propagation and advanced machine learning classifiers can run on constrained on-board hardware.

By shifting the collision avoidance loop from the ground to the edge (the satellite), we eliminate communication latency, enabling satellites to react to threats in real-time. The simulation results indicate a significant reduction in unnecessary maneuvers, preserving the operational life of the satellite.

11.2 Future Work

Several avenues exist for extending this work:

Swarm Coordination: Enabling ASTRIA-equipped satellites to communicate their maneuver plans to neighbors to prevent "evading into" another satellite.

Optical Navigation: Integrating on-board cameras to visually track debris and refine the orbital solution before maneuvering.

Hardware-in-the-Loop (HIL): Testing the code on actual Flight Model (FM) hardware in a vacuum chamber environment.

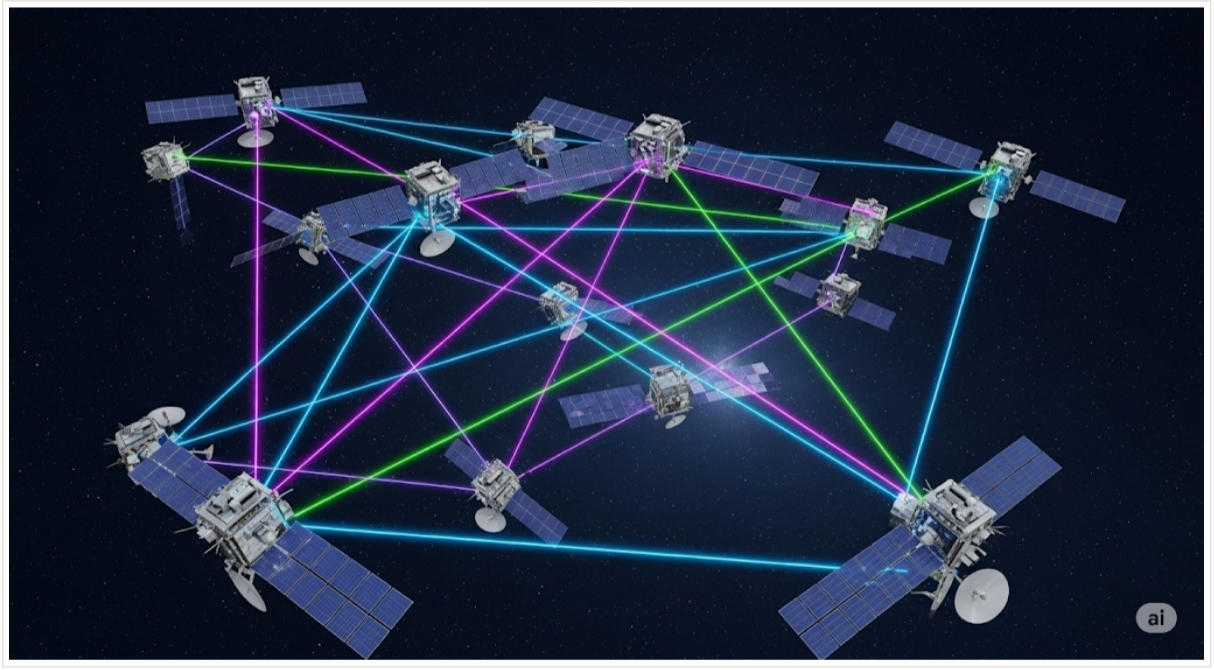

Figure 11.1: Vision of a self-organizing autonomous constellation.

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